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Do Medicare HMOs still reduce health services use after controlling for selection bias?

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Summary

This study models the relationship between Medicare beneficiary decisions to join Medicare HMOs and subsequent health services utilization. The relationship between health plan choice and utilization is thought to be endogenous because of favorable selection into HMOs. Previous studies found significantly lower inpatient utilization among Medicare HMO enrollees than among nonenrollees, but lacked strong controls for selection bias. Thus, a firm conclusion could not be drawn as to whether the observed differences were attributable to the HMO practice setting or to baseline differences in the illness profiles of the two groups studied. The present study uses simultaneous equations methods, including discrete factor estimation, to test the effect of Medicare HMOs on utilization when strong controls for selection bias are imposed. The model was run on a panel of 1993–1996 data from the Medicare Current Beneficiary Survey, supplemented with linked data on Medicare HMO characteristics and area supply characteristics. The study found that even when favorable selection is controlled for, Medicare HMOs significantly reduce both the probability of hospitalization and the number of inpatient days used by those who are hospitalized. Medicare HMOs do not, however, appear to reduce the use of physician services. Copyright © 2002 John Wiley & Sons, Ltd.

Keywords managed care; selection bias; MCBS; physician use; hospital use

Introduction

The aging of the United States population combined with the increasing per capita cost of health care has seriously strained the Medicare program's ability to ensure the future provision of health care for aged and disabled persons covered by the program. As part of an effort by the Health Care Financing Administration (HCFA now called the Centers for Medicare and Medicaid Services [CMS]) effort to contain costs, a partial system of prospective capitation was implemented in the Medicare program in 1985. Under the Medicare risk program, now called Medicare +Choice, CMS disburses a monthly capitated payment to qualified health maintenance organizations (HMOs) that contract with CMS to provide comprehensive health services to Medicare beneficiaries who choose to join them. Enrollment in the Medicare risk program has grown slowly over the last 15 years, reaching 17% of enrollees in 1998 [1].

In the last decade, numerous attempts have been made to evaluate the success of the Medicare risk

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program in reducing the costs of care for elderly Americans. These analyses consistently have encountered confounding problems due to the possibility of biased selection of beneficiaries into Medicare HMOs. By law, all Medicare beneficiaries except persons with pre-existing end-stage renal disease are permitted to choose whether or not to enroll in a Medicare HMO. It is possible that those beneficiaries who choose to join an HMO and those who remain in a traditional plan differ significantly with respect to their health status, health care needs, or propensity to consume care. If this is the case, then observed differences in health services utilization in HMOs and fee-for-service plans may be due not to more efficient provision of care in one of the plans, but rather to baseline differences in the health of their insured populations. If Medicare HMOs attract a disproportionate share of the relatively healthy, then *favorable selection* is said to have occurred. If Medicare HMO enrollees are, on average, less healthy than nonenrollees, then *adverse selection* into Medicare HMOs has occurred.

CMS use a limited set of risk adjusters in the Adjusted Average Per Capita Cost (AAPCC) payment formula to control for selection bias on certain sociodemographic characteristics – namely, age, gender, disability status, institutional status, employment status, and Medicaid eligibility. However, studies consistently have found evidence of biased selection on omitted risk factors, such as major medical diagnoses, functional status, pre-HMO-enrollment utilization, and self-reported health status. Studies from the early years of Medicare risk contracting uniformly found evidence of strong favorable selection on these characteristics [2–6]. Evidence also indicates that favorable selection persisted through the late 1980s [7–10].

In econometric terms, the phenomenon of favorable selection creates a problem of endogeneity in models of health services utilization. If unobservable aspects of a Medicare beneficiary's health status affect both her choice of health plan (HMO or fee-for-service) and her subsequent health services utilization, then the relationship between plan choice and utilization is endogenous. A single-equation model of health services utilization with health plan choice as an explanatory variable would result in biased estimates under these circumstances. For this reason, single-equation methods have been unable to determine whether the lower observed levels of utilization in Medicare HMOs are due to genuine efficiencies in the process of care or merely to the fact that HMO enrollees are healthier than the fee-for-service population to begin with.

This study uses simultaneous equations methods to test the effect of Medicare HMOs on utilization when controls for selection bias are imposed. Simultaneous equation techniques were not used in earlier investigations due to the lack of identifying variables. Identification of the health utilization equations is achieved here by assuming that Medicare HMO market penetration affects health plan choice, which subsequently affects health utilization. We hypothesized that Medicare risk HMO enrollees would have slightly lower health services utilization than nonenrollees after controlling for sociodemographic and health status differences. The magnitude of the effect was expected to be smaller than that observed in studies of the early years of the Medicare risk program, because those studies did not employ strong controls for favorable selection and because favorable selection may have diminished over time.

The simultaneous equations model was run on a panel of linked 1993–1996 data from the Medicare Current Beneficiary Survey, the Bureau of Health Professions Area Resource File, and Medicare administrative datasets. A discrete factor estimation on a panel of 38 185 observations constituted the main analysis. The robustness of the results to changes in the sample composition and estimation method was tested using traditional instrumental variables estimation techniques as well as a smaller panel dataset.

The study contributes to the empirical investigation of HMO efficiencies in two respects. First, the use of market penetration variables to achieve identification in a simultaneous equations model of HMO selection is an advancement over the single-equation models of previous studies. Second, we use discrete factor estimation, a relatively new technique, to control for unobserved heterogeneity in the simultaneous equations.

Background

Effect of HMOs on utilization

Empirical evidence suggests that HMOs can significantly reduce health care expenditures relative to fee-for-service care. In interpreting studies of utilization in HMOs, it is important to be cognizant of possible problems of confounding due to favorable selection. Strong evidence of the cost-saving effects of HMOs comes from the RAND Health Insurance Experiment, a randomized controlled trial [11]. Nonrandomized studies provide only mixed support, however, for the proposition that HMOs reduce hospital length of stay [12–14]. Luft's review of 26 studies of utilization in HMOs and fee-for-service arrangements concluded that HMO enrollees used 10–40% fewer hospital days than fee-for-service insureds, but that the difference was due to lower admission rates and not shorter length of stay [12]. Many of the studies in Luft's review did not provide strong controls for health status, however. More recent studies also tend to find that HMO managed care plans reduce hospitalization, but the studies suffer from possible selection bias and focus on a few specific plans, making generalization difficult (see Glied [15] for a review).

There is no clear evidence that HMOs realize significant reductions in the use of outpatient and physician services. In the RAND study, the HMO and fee-for-service groups had similar numbers of outpatient visits. The studies reviewed by Luft also failed to find a significant difference in the number of physician visits between HMO and fee-for-service patients [12].

Empirical studies of the effectiveness of HMOs in reducing costs for elderly patients have found much stronger effects. A study of nine HMOs operating in the early years of the Medicare risk program found that although no cost reductions were observed in the first year of study, reductions of 14–25% were observed in the second year, for an overall cost savings of about 8% [5]. The savings were due to fewer admissions rather than shorter length of stay. Another study of 22 Medicare HMOs also found that hospital use rates were considerably lower in the HMOs than among fee-for-service beneficiaries [16]. However, the study did not provide strong controls for differences in the baseline health of the two groups. A more recent study reported that Medicare HMOs shortened the average hospital length of stay by 16.8% relative to fee-for-service, but did not reduce the number of admissions [17]. The general finding of lower costs in more recent studies applies to all forms of managed care, not just integrated plans [15].

The effects of Medicare HMOs on outpatient utilization for elderly patients appear to be complex. Brown and colleagues found that, after controlling for possible differences in health status between HMO enrollees and nonenrollees, HMO enrollees had a 5% higher probability of seeing a physician at least once during the year, but a slightly lower probability of having one or more physician visits per month [17].

Modeling the relationship between health plan choice and utilization

Existing studies of utilization in Medicare HMOs have not used simultaneous equations, but rather have employed one of three approaches: (1) single-equation models of utilization; (2) sample selection models developed by Heckman [18] and Lee [19]; and (3) a longitudinal approach proposed by Hornbrook *et al.* [20]. Because of the endogeneity between health plan choice and utilization, the single-equation approach cannot disentangle reductions in utilization due to HMO efficiencies from lower levels of utilization due to HMO enrollees' disproportionately better baseline health status. The sample selection approach is a significant improvement over single-equation methods, but sample selection models have been criticized for their instability and their assumption of a bivariate normal distribution for the error terms of the HMO choice and utilization equations [20].

The longitudinal approach involves first ascertaining whether selection bias exists by performing separate OLS estimations of utilization for persons who switch from fee-for-service to HMOs and for persons who stay with fee-for-service; then comparing the coefficients using a Chow [21] test; and then testing the effects of HMO membership on utilization by running the utilization model twice on the switchers, once in the year prior to switching and once in the first HMO year, and comparing the coefficients. This approach suffers from several shortcomings, including bias due to the use of OLS to estimate utilization when there may be a large proportion of observations clustered at zero; the possibility that utilization may be atypically high or low in the first year after joining an HMO; and the conceptual problems with measuring selection bias by trying to detect differences in the relationships between various health status measures and utilization, rather than by modeling plan choice itself.

Hornbrook *et al.* [20] stated that a simultaneous system approach would be preferable to their approach, but that the use of simultaneous equations was not possible due to a lack of variables to achieve identification of the utilization equation. The simultaneous equations approach achieves the strong control for selection bias obtained by the Heckman/Lee model, but is more robust to distributional assumptions about the errors [22]. The discrete factor model used in this estimation is particularly advantageous in this regard, because its semiparametric specification avoids the problems associated with assuming joint normality of the error terms, while still obtaining identification from instrumental variables.

Empirical model

Conceptual framework

The empirical model of health plan choice and health services utilization in this study is grounded in the theory of consumer choice. It conceives of enrollment in a Medicare HMO as a voluntary choice made by Medicare beneficiaries on the basis of a comparison of the costs, risks, and benefits of HMO membership relative to remaining in a fee-for-service plan. A consumer's choice in this regard is theorized to be affected by both the personal characteristics of the decision maker – including health status, sociodemographic characteristics, and personal financial resources – and the characteristics of the local Medicare health plan market – including the range of HMO options available in the market and the extent of managed care penetration. A consumer's health services utilization is also modeled as a function of both personal and market characteristics. An individual's propensity to consume health services is influenced by sociodemographic characteristics, the individual's financial resources, and the individual's perceived health status and major diagnoses. Additionally, propensity to consume health services is affected by the supply of physicians and hospital services available in the local market.

In this conceptual model, health status and sociodemographic characteristics associated with health services utilization influence both a Medicare beneficiary's health plan choice and her subsequent utilization. Medicare HMO market penetration and the HMO options available to a beneficiary in a particular market affect health plan choice, but do not significantly affect utilization, conditional upon plan choice. Conversely, the supply of physicians and hospitals in the market affects utilization, but not health plan choice. Health plan choice affects utilization. Finally, unobserved variables representing unmeasured aspects of health status and propensity to consume care affect both HMO choice and utilization.

This conceptual framework is captured in the following empirical model, which consists of a health plan choice equation and three separate measures of utilization:

$$C_{it} = \alpha_0 + \alpha_1 H_{i(t-1)} + \alpha_2 S_{it} + \alpha_4 M_{it} + \alpha_5 Z_{it} + v_{1it} \tag{1}$$

$$\Pr(I_{it} > 0) = \beta_0 + \beta_1 C_{it} + \beta_2 H_{it} + \beta_3 S_{it} + \beta_4 A_{it} + \beta_5 Z_{it} + v_{2it} \tag{2}$$

$$\ln I_{it} | I_{it} > 0 = \theta_0 + \theta_1 C_{it} + \theta_2 H_{it} + \theta_3 S_{it} + \theta_4 A_{it} + \theta_5 Z_{it} + v_{2'it} \tag{2'}$$

$$\Pr(P_{it}) = \delta_0 + \delta_1 C_{it} + \delta_2 H_{it} + \delta S_{it} + \delta_4 A_{it} + \delta_5 Z_{it} + v_{2''it} \tag{2''}$$

where C is the health plan choice dummy (1 = medicare HMO), I the inpatient utilization (hospital days), P the physician utilization dummy (1 = at least one physician visit), H the vector of health status variables, S the vector of sociodemographic characteristics, M the vector of HMO market characteristics, Z the vector of control variables, A the vector of area health services supply variables, and α, β, θ, and δ, are parameters to be estimated, v is the error term, i indexes individuals, and t indexes time. The error term is decomposed into a stochastic time-varying component e and a permanent factor u that captures the dependence across equations at each point in time and the dependence across time periods and equations. This approach, which is described more fully in the next section, controls for the endogeneity of health plan choice in the utilization equations. A random effects specification was used to apply the model to a panel of 4 years of data.

Inpatient utilization is modeled using a two-part model [23], which consists of two functionally separable estimations of the probability of hospitalization and the logged number of inpatient days conditional upon hospitalization. This model was necessary due to the skewed distribution of hospital days – over 80% of observations had no hospital use in each of the years under study. The use of a permanent factor in the error term controls for the correlation of the errors in the two-part model, effectively controlling for potential sample selection biases in the conditional inpatient days equation. Due to data constraints, use of physician services is modeled as a simply binary indicator of whether or not the individual had at least one physician visit during the year.

The vector of health status variables in the models consisted of general health status self-rating, activities of daily living (ADLs), instrumental activities of daily living (IADLs), presence of several major chronic conditions, and whether health limits the individual's social life. These health status variables were lagged by 1 year in the health plan choice equation in order to reduce possible endogeneity. The vector of sociodemographic variables consisted of age, education, race, sex, marital status, nursing home residence, usual source of care, income, Medicaid eligibility, and Medigap coverage. The vector of HMO market characteristics included the number of Medicare HMOs in the county, percent penetration (percentage of Medicare beneficiaries enrolled in a Medicare HMO), and whether an IPA-model HMO was available in the county. The vector of area health services supply characteristics consisted of the county physician-to-population ratio and hospital-bed-to-population ratio. The control variables consisted of the census region, rural/urban residence, the year of the observation, and the base county AAPCC rate.

The first equation in the system, the health plan choice equation, contains only exogenous variables on the right-hand side. The three utilization equations, however, have health plan choice as an endogenous explanatory variable. The system is identified through exclusion restrictions. A vector of nine market penetration variables (three main effects and six interactions of market penetration with health status measures) are included in the HMO choice equation but excluded from the utilization equations, resulting in overidentification of the equations. The three main effects are the number of HMOs in a county, HMO market penetration in a county, and whether an IPA model HMO is available in a county. These variables were interacted with dummy variables for self-reports of "excellent health" and "poor health". The main instruments are plausible in the sense that greater availability of HMOs or higher levels of enrollment by others in the area should increase the likelihood that any given individual enrolls in an HMO, but should not affect the utilization of health services. While health status undoubtedly affects utilization, the interactions of the health status measures with the HMO availability or penetration measures are plausible as instruments in the sense that the effects of greater availability or penetration may be mitigated or intensified by an individual's health status.

Discrete factor model

The system was estimated using a discrete factor model that controls for the simultaneous relationship between the equations by approximating the effects that are common but unobservable across equations [24]. The discrete factor model has been used in health economics research by Goldman [25] to model the endogenous relationship between health plan choice and utilization, and by Cutler [26] to model mortality and readmission rates. A useful overview of the theoretical basis of the model is provided by Mroz [27]. In brief, the discrete factor model decomposes the errors in a two-equation system

$$Y_{1it} = \alpha X_{1it} + v_{1it} \quad \text{(health plan choice equation)}$$

$$Y_{2it} = \beta X_{2it} + v_{2it} \quad \text{(utilization equation)}$$

into uncorrelated and correlated components:

$$v_{1it} = \rho_1 u_i + e_{1it}$$

$$v_{2it} = \rho_2 u_i + e_{2it}$$

where u, e_1 and e_2 are mutually independent and are independent of the exogenous variables in the model. The uncorrelated components e_1 and e_2 are assumed to be distributed normally with mean zero and standard deviation σ_1 and σ_2, respectively. A discrete distribution is assumed for the correlated component u. This component represents the unobservable heterogeneity that causes the correlation across equations and time periods. In this study, it represents chronic or permanent health conditions that, we theorize, make individuals less likely to join a Medicare HMO, more likely to have some hospital and physician use, and likely to have a higher level of hospital use conditional upon having some use. This unobserved factor is constant across equations for an individual and also constant over time since the health condition is chronic in nature. The model permits correlation of the dependent variables at each point in time, as well as correlations across time, on this permanent factor. The relationship between the permanent factor and the dependent variables is assumed to be linear.

The joint distribution of v_1 and v_2 conditional on the value taken by the permanent factor u is

$$f(v_1, v_2|u) = \frac{1}{\sigma_1}\phi\left(\frac{Y_1 - \alpha X_1 - \rho_1 u}{\sigma_1}\right) \times \frac{1}{\sigma_2}\phi\left(\frac{Y_2 - \beta X_2 - \rho_2 u}{\sigma_2}\right)$$

where ϕ is the standard normal density function. The unconditional joint distribution of the errors is

$$f(v_1, v_2) = \int f(v_1, v_2|u)\,\mathrm{d}F(u)$$

where $F(u)$ is the cumulative distribution function of u.

The discrete factor model uses a variable number of discrete parameters (mass points) to approximate this cumulative distribution. The joint distribution of the errors is

$$f(v_1, v_2) = \sum_{m=1}^{M} \omega_m \frac{1}{\sigma_1}\phi\left(\frac{Y_1 - \alpha X_1 - \rho_1 \eta_m}{\sigma_1}\right) \times \frac{1}{\sigma_2}\phi\left(\frac{Y_2 - \beta X_2 - \rho_2 \eta_m}{\sigma_2}\right)$$

where M is the number of mass points. In this study, the distribution of the u_i was approximated using five mass points ($M = 5$). The values of the first and last mass points m_1 and m_5 were normalized to 0 and 1, respectively. The η_m in the above equation represent the mass point values and the ω_m represent the probability that u takes on the value of each mass point ($\Pr(u = \eta_m)$). If the η_m are formulated as

$$\eta_m = \frac{e^{\lambda_k}}{1 + \sum_{k=1}^{M-2} e^{\lambda_k}}$$

then the probability corresponding to each η_m is

$$\omega_m = \frac{e^{\varphi_j}}{1 + \sum_{j=1}^{M-1} e^{\varphi_j}}.$$

The discrete factor model estimates the λ_k's and the φ_j's, from which the mass point values (other than the first and last points) and the probability weights associated with each mass point are calculated. These discrete factors are estimated at both the cluster and the individual level. In this study, the GQOPT subroutine in FORTRAN was used for the optimization. Starting values for the algorithm were derived from instrumental variables estimations.

The advantage of the discrete factor model is that it relaxes the parametric assumptions of the traditional instrumental variables approach to simultaneous equations estimation. Goldman [25] notes that these assumptions may be the reason that previous studies of the interdependence of health plan choice and utilization sometimes have failed to identify a selection effect in HMOs. Monte Carlo evidence shows that discrete factor estimates are comparable to maximum likelihood in terms of unbiasedness, but often superior in terms of efficiency [27].

Data

Data sources

The model was run on a panel of 4 years of data (1993–1996) from the Medicare Current Beneficiary Survey (MCBS), supplemented with linked county-level data from the Area Resource File, the Medicare Market Penetration File, and the Medicare Prepaid Health Plans Monthly Report. The MCBS Cost and Use Files for 1993–1995 and the MCBS Access to Care File for 1996 were used.

Individuals residing in counties not served by at least one Medicare HMO were excluded from the analysis, since they had no option to join a Medicare HMO. Also excluded were persons under age 65, residents of Puerto Rico, and persons with end-stage renal disease (who are not permitted to join Medicare HMOs). Nine hundred seventy-two persons who switched between an HMO and a fee-for-service plan during a given year were excluded for the year of their switching only. After these exclusions, the panel consisted of 38 185 observations representing 21 965 individuals. The dataset included persons who died and persons lost to MCBS follow-up during the 1993–1996 period. Inpatient days data were rescaled to an annual estimate for persons who died during the year to account for the fact that they did not have a chance to incur a full year's utilization.

To test the robustness of the regression results to changes in the sample composition and estimation methods, the models were rerun using instrumental variables estimation on both the main panel and a smaller panel of 7432 observations representing persons who were present in the MCBS sample for the entire 1993–1996 period. This sample consisted of continuously enrolled Medicare beneficiaries, i.e., it did not include persons who died or became newly eligible for Medicare during the year.

The large panel rather than the small panel is reported here for three reasons. First, because the small panel excludes persons who died, results from that estimation are not generalizable to the Medicare population as a whole. The inclusion of persons approaching death is of clear interest in models estimating health care utilization and expenses for the Medicare program. Second, the number of HMO enrollees with hospitalizations was very low in the small sample (43 out of the sample of 7432 persons), creating a problem of perfect prediction in the probability of hospitalization model. This made it necessary to exclude some variables of interest from that model and collapse other variables into a smaller number of categories, making the model less than fully specified in the small panel analysis. Finally, the statistical power of the small panel analysis is significantly lower than that of the large panel estimation.

Descriptive statistics

Table 1 presents the descriptive statistics over all observations. An examination of the descriptive statistics broken down by year (not presented) showed that most figures were stable over the study period. However, because the MCBS oversampled HMO members in 1996 and HMO members tended to be younger and somewhat healthier than fee-for-service beneficiaries, the 1996 sample was slightly healthier on some health status measures than the 1993 sample.

A review of the descriptive statistics reveals a sample of fairly healthy, functional elderly Medicare beneficiaries of mean age 72.5 years. In 1993, the individuals in the dataset were approximately 61% female, 88% white, and 71% educated at the high school level or less. About 70% of individuals resided in a large or medium sized metropolitan area. About 35% of the observations had an annual income below $10 000, and about 84% had an income below $30 000. In 1993, approximately 5% of the sample were Medicare risk HMO enrollees for the entire year, while 95% were in fee-for-service settings for the entire year. The percentage of HMO enrollees rose over the study period, and in the 1996 oversample was as high as 22%. In 1993, 67% of the observations in the dataset had a Medigap plan and approximately 13% were Medicaid recipients.

The individuals in the dataset generally perceived themselves to be in good health; only 8% reported that their heath status was poor. Except for hypertension and arthritis, chronic conditions were fairly rare. Most of the individuals reported being able to perform most ADLs and IADLs. In 1993, 21% of the observations in the dataset had one or more hospital days, and among those with at least one hospitalization, the mean number of annual inpatient days was 17.43 days. Approximately 77% of the dataset had at least one physician visit during the year.

Crosstabulations and *t*-test results verified that on average, HMO enrollees in counties with high HMO market penetration were not significantly sicker, relative to the average fee-for-service patient, than HMO enrollees in low-penetration counties. This is important because if the marginal HMO enrollee in high-penetration counties was sicker than the marginal enrollee in low-penetration counties, this would suggest that utilization and market penetration are correlated and thus that market penetration may be a poor instrument for identifying the utilization equations.

Seven hundred twenty-five counties were represented in the dataset. Observations were spread fairly evenly over the continental US, with some concentration in the Atlantic states. Ninety-five percent of the observations were persons who lived in counties in which an IPA-model Medicare

Table 1. Sample descriptive statistics ($n = 31\,185$ observations, 21 965 persons)[a]

Dependent variables		
HMO member		4642 (12.16%)
Some inpatient use		7338 (19.22%)
No. of inpatient days (for those hospitalized)	Mean	13.66 (s.d. 21.26)
Some physician use		29 963 (78.47%)
Sociodemographics		
Age	65–74	15 388 (40.30%)
	75–84	15 236 (39.90%)
	85+	7561 (19.80%)
Sex	Male	15 179 (39.75%)
Race	White	33 698 (88.25%)
	Black	3466 (9.08%)
	Other	1021 (2.67%)
Education	<High school	9730 (25.48%)
	High school	17 397 (45.56%)
	Some college	9964 (26.09%)
	Missing	1094 (2.97%)
Income	<$10 000	11 716 (30.68%)
	$10 000–$30 000	19 241 (50.39%)
	$30 000–$50 000	4536 (11.88%)
	>$50 000	1861 (4.87%)
	Missing	831 (2.18%)
Medigap	Yes	24 765 (64.86%)
	No	12 839 (33.62%)
	Missing	581 (1.52%)
Medicaid		4881 (12.78%)
Nursing home resident		3496 (9.16%)
Usual source of care		33 518 (8.78%)
Health Status		
Self-perceived health	Excellent/very good	16 157 (42.31%)
	Good/fair	19 157 (50.17%)
	Poor	2871 (7.52%)
ADLs	Mean	4.95 (s.d. 1.77)
IADLs	Mean	4.66 (s.d. 1.98)
Health limits social life		13 816 (36.18%)
History of arthritis		21 729 (56.91%)
History of rheumatoid arthritis		5166 (13.53%)
History of atherosclerosis		6120 (16.03%)
History of broken hip		2618 (6.86%)
History of cancer		1463 (20%)
History of coronary heart disease		6623 (17.35%)
History of skin cancer		6846 (17.93%)
History of diabetes		6150 (16.11%)
History of emphysema/COPD		5425 (14.21%)
History of high blood pressure		20 590 (53.92%)
History of myocardial infarction		6047 (15.84%)
History of osteoporosis		4457 (11.67%)
History of other heart problem		12 020 (31.48%)
History of Parkinson's Disease		784 (2.05%)
History of partial paralysis		2585 (6.77%)
History of stroke		5229 (13.69%)
HMO Market Characteristics		
Number of HMOs in county	Mean	25.37 (s.d. 25.61)
Percent penetration	Mean	9.0 (s.d. 12.80)
IPA model HMO in county		36164 (94.71%)
Area Supply Characteristics		
Physician-to-population ratio	Mean	0.0026 (s.d. 0.0016)
Hospital bed-to-population ratio	Mean	0.0044 (s.d. 0.0026)

[a] Means and proportions over all observations (not individuals).

HMO was operating. The average number of Medicare HMOs operating in a county in 1993 was 15, and the average market share of Medicare HMOs in a county was approximately 5%. By 1996, these averages had risen to 25 HMOs and nearly 14% penetration.

Results

Model diagnostics

A test described by Pindyck and Rubinfeld [28] was used to test the exogeneity of the HMO choice variable. The results were quite unexpected: The HMO choice variable was found not to be endogenous for any of the utilization models using the big panel dataset. Theory, as well as empirical findings in the literature to date, strongly suggest that endogeneity exists between HMO choice and subsequent health services utilization. One possible explanation is that the Pindyck–Rubinfeld test did not detect endogeneity because that test was designed with linear models in mind and was here applied in a nonlinear framework.

Two tests of the instrumental variables were performed. In the first test, a Wald test was used to determine whether the instruments were correlated with the potentially endogenous variable (HMO choice) [29]. The Wald test determined that the nine market penetration variables (including the six interaction terms) were jointly significant in the HMO choice equation ($\chi^2(9) = 547.15$, $p<0.01$), indicating that they passed the first test.

The second arm of the instrumental variables test examined whether the instruments could validly be excluded from the main equation (utilization). The second equation was run including actual (not predicted) values of the endogenous variable plus all of the instruments, and a Wald test was performed on the instruments. If the instruments are jointly significant, then they fail the overidentification test. The results indicated that the nine instruments collectively constituted good instruments for the probability of hospitalization equation and the physician visits equation, but not for the inpatient days model: $\chi^2(9) = 14.18$, $p = 0.12$ for the probability of hospitalization model; $\chi^2(9) = 11.76$, $p = 0.23$ for the physician visits model; and $\chi^2(9) = 27.38$, $p<0.01$ for the inpatient days model.

It is difficult to account for why the market penetration indicators were found jointly to be a significant predictor of the number of hospital days, but not the probability of hospitalization. The signs of the coefficients on these variables differed in a way that is not theoretically explicable: The "percent HMO penetration" variable had a negative and statistically significant coefficient ($\beta = -1.24$, $p<0.01$), while the "number of Medicare HMOs" variable had a positive and statistically significant coefficient ($\beta = 0.00303$, $p<0.01$). Only two of the six interaction terms were individually significant at the 5 percent level. In short, although the specification test indicates that these variables jointly are significant predictors of inpatient days, no clear theoretical rationale for this result emerges. The result is cause for some concern as regards the identification of the inpatient days equation, however.

A potential problem with the use of market penetration as an instrument in this system of equations is that it may be correlated with utilization in the sense that HMOs may choose to locate in counties with high or low utilization by fee-for-service patients. In order to investigate this possibility, a number of tests were performed. First, utilization levels in counties at high and low market penetration levels were compared using a t-test. While significant differences were observed ($p<0.01$ for all three utilization variables), it is possible that differences in utilization levels are largely attributable to the urban/rural status of the county, which is highly correlated with HMO market penetration, rather than to market penetration itself. As a result, it is problematic to draw inferences from a t-test.

To control for the possibility that rural/urban status may be responsible for much of the observed correlation, the utilization regression models were rerun with penetration included as a continuous explanatory variable. The penetration variable was not statistically significant in the probability of hospitalization model or the conditional inpatient days model, but it was significant in the physician visits model ($\beta = 0.39$, $p = 0.007$).

To further investigate the relationship between utilization and market penetration, a model was run regressing utilization on future market penetration:

$$\text{utilization}_{it} = \beta X_{it} + \alpha(\text{penetration}_{i(t+k)}) + v_{it}$$

The model was run three times for each utilization variable using penetration data from year $t+1$, $t+2$, and $t+3$. The penetration variable only achieved statistical significance in one of the nine regressions.

Because HMO location decisions are influenced by AAPCC rates, which are in turn related to historical levels of fee-for-service utilization, a model was also run to determine whether there is a residual effect of utilization levels on penetration after controlling for AAPCC rate. The regression

$$\text{penetration}_{t+k} = \beta X_{it} + \alpha(\text{utilization}_t) + \delta(\text{AAPCC}_t) + v_{it}$$

was run three times for each utilization variable using penetration data from years $t+1$, $t+2$, and $t+3$. Utilization only achieved statistical significance in one of the nine estimations. In contrast, AAPCC rate was statistically significant at the 1% level in all estimations. This analysis indicates that while AAPCC rate is a highly significant predictor of future market penetration, utilization is by most measures not a statistically significant predictor of future market penetration after controlling for AAPCC rate. Taken together, these several analyses provide evidence that utilization is not strongly associated with HMO market penetration, and thus it is reasonable to use penetration as an instrument in this system of equations.

Regression results

A naïve model was run in order to provide baseline estimates from which to judge the gains associated with a simultaneous equations modeling approach. The naïve model consisted of random effects probit and OLS estimations with Huber/White corrections to the standard errors. That is, the naïve model accounted for the panel data structure but did not account for the endogeneity of the HMO variable. For the probability of hospitalization model, the coefficient on the HMO variable is -0.511 ($p<0.001$), indicating that the HMO practice setting significantly reduces the probability of hospitalization as compared to the fee-for-service setting. For the inpatient days equation, $\beta = -0.212$ ($p = 0.002$). Thus, Medicare HMOs also significantly reduces the number of hospital days used by those hospitalized. The HMO variable is also statistically significant in the physician visits model, but its sign is positive ($\beta = 0.245$, $p<0.001$). HMO membership significantly increases the probability of having at least one physician visit during the year.

Regression results for the discrete factor estimation are presented in Tables 2 and 3. The probability weight and mass point results for the discrete factor model are reported in Tables 4–6. The coefficients in Tables 2 and 3 for the binary equations are interpreted in the same way as regular logit coefficients; those for the inpatient days equation may be interpreted in the same way as regular OLS coefficients. However, computing predicted probabilities requires a special procedure for discrete factor results in order to incorporate the heterogeneity term. The predicted probability for each observation consists of the weighted mean of $X\beta$ multiplied by the probabilities associated with each of the individual-level and cluster-level mass points in the discrete distribution estimated by the model. Obtaining the predicted values for the inpatient days model entails a similar procedure plus retransformation via a smearing adjustment.

The coefficients on the health status variables in the health plan choice equation (see Table 2) indicate the extent to which favorable selection persists in Medicare HMOs. These results suggest that there is some favorable selection in HMO enrollment. The excellent self-reported health status variable is positively signed and statistically significant at the 5% level. Poor self-reported health and the ''health limits social life'' variable are negatively signed but not significant. Having a history of stroke significantly decreases the probability of joining an HMO, as does advanced age and nursing home residence. High HMO market penetration significantly increases the probability of HMO membership, but based on the coefficients on the market penetration interaction terms, the extent of market penetration in a county does not appear to have a strong effect on the degree of favorable selection into HMOs in that market. The finding of favorable selection in Medicare HMO enrollment is consistent with studies from the 1980s, as well as a recent study by Hamilton [10] finding that Medicare HMO enrollees are less likely than patients who did not join HMOs to have had positive health care expenditures in the year prior to HMO enrollment.

The results of the present study indicate that HMO membership has a negative and statistically significant effect on the probability of hospitalization ($\beta = -1.146$, $p<0.01$, see Table 3). The magnitude of the effect of an explanatory variable on a dependent variable can be demonstrated by comparing the mean predicted values of the dependent variable when all observations in the dataset are coded to take on one value or the other of the explanatory variable. Predicted values of each of the utilization variables corresponding to enrollment in fee-for-service and enrollment in an

Table 2. Regression results: health plan choice equation (discrete factor estimation, $n = 38\,185$)[a,b]

	Coeff.	Robust s.e.
Constant	4.843**	(1.063)
Market penetration		
Percent penetration	21.069**	(2.104)
Number of HMOs	−0.0345**	(0.0042)
Penetration * Excellent health^L	−0.86	(0.77)
Penetration * Poor health^L	0.49	(1.60)
Penetration * Number of chronic conditions^L	−0.33**	(0.13)
Penetration * Health limitations on social life^L	0.32	(0.88)
Penetration * ADLs^L	0.57	(0.38)
Penetration * IADLs^L	−0.03	(0.35)
IPA plan available	0.23	(0.73)
Health and functional status		
Excellent health^L	0.44*	(0.20)
Poor health^L	−0.53	(0.42)
ADLs^L	−0.012	(0.095)
IADLs^L	0.021	(0.091)
Health limitations on social life^L	−0.24	(0.23)
History of arthritis^L	0.28*	(0.12)
History of cancer^L	−0.29	(0.16)
History of stroke^L	−0.538**	(0.202)
Demographics		
AAPCC adjustors		
Age 75 to 84	−0.47**	(0.12)
Age 85+	−0.87**	(0.18)
Male	0.10	(0.12)
Medicaid recipient	−5.02**	(0.30)
Nursing home resident	−1.37**	(0.37)
Other		
Less than high school education	−0.43**	(0.16)
Some college	−0.41**	(0.14)
Medigap policy^L	−5.66**	(0.24)
Black	0.08	(0.20)
Other nonwhite race	−0.37	(0.28)
Married	0.36**	(0.13)
Has a usual source of care	1.95**	(0.23)
Income < \$10 000	0.14	(0.14)
Income \$30 001–\$50 000	−0.52**	(0.16)
Income > \$50 000	−0.89**	(0.25)

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level.
[a] *Omitted from table*: results for census region, rural/urban residence, year of observation, AAPCC rate.
[b] X^L = Variable lagged by one year.

HMO, including estimates from the naïve model, are provided in Table 7. When all observations are recoded to take on a "no" value for the HMO membership variable, the average of the predicted probabilities is 18.8%. When all are recoded to "yes," the probability decreases to 7.58 percent, a decrease of 11.2 percentage points (59.6%).

The results show that HMO membership significantly decreases the number of hospital days for those hospitalized ($\beta = -0.696$, $p < 0.01$, see Table 3). The mean predicted number of hospital days for those hospitalized is 13.3 days. The mean when all observations are coded with a "no" value for HMO membership is 13.5 days; when all are

Table 3. Regression results: utilization equations[a]

	Probability of Hospitalization (Discrete factor estimation, $n = 38\,185$)		Number of Inpatient Days (Discrete factor estimation, $n = 7338$)[b]		Probability of Physician Visit (Discrete factor estimation, $n = 38\,003$)[c]	
	Coeff.	Robust s.e.	Coeff.	Robust s.e.	Coeff.	Robust s.e.
Constant	−2.26**	(0.18)	2.53**	(0.14)	−5.36**	(0.29)
HMO membership	−1.146**	(0.089)	−0.696**	(0.077)	2.37**	(0.11)
Health and functional status						
Excellent health	−0.319**	(0.035)	−0.038	(0.032)	−0.314**	(0.048)
Poor health	0.328**	(0.048)	0.212**	(0.037)	−0.325**	(0.088)
ADLs	−0.046**	(0.013)	−0.001	(0.010)	0.082**	(0.022)
IADLs	−0.088**	(0.012)	−0.0853**	(0.0101)	0.1183**	(0.0206)
Health limitations on social life	0.547**	(0.033)	0.165**	(0.028)	0.225**	(0.054)
History of arthritis	−0.024	(0.031)	−0.044	(0.027)	0.531**	(0.046)
History of rheumatoid arthritis	−0.056	(0.040)	−0.023	(0.034)	0.289**	(0.068)
History of atherosclerosis	−0.039	(0.038)	−0.037	(0.032)	0.068	(0.068)
History of broken hip	0.2878**	(0.0508)	0.066	(0.041)	−0.046	(0.094)
History of cancer	0.227**	(0.034)	0.038	(0.029)	0.288**	(0.059)
History of coronary heart disease	0.119**	(0.039)	−0.034	(0.032)	0.27**	(0.072)
History of skin cancer	−0.124**	(0.039)	−0.052	(0.034)	0.381**	(0.062)
History of diabetes	0.191**	(0.036)	0.104**	(0.031)	0.363**	(0.065)
History of emphysema/COPD	0.207**	(0.038)	0.128**	(0.032)	0.354**	(0.067)
History of high blood pressure	0.0972**	(0.0301)	−0.01	(0.026)	0.614**	(0.045)
History of myocardial infarction	0.459**	(0.038)	0.074*	(0.031)	−0.061	(0.069)
History of osteoporosis	−0.039	(0.044)	0.028	(0.038)	0.323**	(0.079)
History of other heart problem	0.332**	(0.031)	−0.004	(0.027)	0.293**	(0.054)
History of Parkinson's Disease	−0.047	(0.086)	−0.074	(0.070)	0.36*	(0.17)
History of partial paralysis	−0.186**	(0.055)	0.030	(0.045)	−0.08	(0.098)
History of stroke	0.219**	(0.041)	−0.008	(0.033)	−0.049	(0.075)
Demographics						
Age 75 to 84	0.192**	(0.034)	0.035	(0.0306)	0.107*	(0.049)
Age 85+	0.211**	(0.044)	−0.098**	(0.038)	−0.047	(0.068)
Less than high school education	−0.008	(0.036)	0.036	(0.031)	0.02	(0.056)
Some college	−0.103**	(0.039)	−0.010	(0.035)	0.223**	(0.057)
Medigap policy	0.279**	(0.042)	0.026	(0.035)	1.2008**	(0.0602)
Black	−0.077	(0.054)	0.152**	(0.047)	−0.484**	(0.076)
Other nonwhite race	−0.150	(0.095)	−0.093	(0.084)	−0.24	(0.12)
Male	0.205**	(0.034)	0.117**	(0.030)	−0.239**	(0.049)
Married	−0.096**	(0.035)	0.1117**	(0.0306)	0.096	(0.051)
Nursing home resident	0.683**	(0.070)	0.397**	(0.050)	−4.64**	(0.14)
Has a usual source of care	0.677**	(0.059)	0.068	(0.048)	2.225**	(0.066)
Income <$10 000	0.045	(0.038)	0.075*	(0.033)	−0.173**	(0.056)
Income $30 001–$50 000	−0.025	(0.051)	−0.084	(0.046)	0.188**	(0.072)
Income >$50 000	−0.131	(0.08)	−0.163*	(0.074)	0.305**	(0.108)
Medicaid recipient	0.046	(0.051)	−0.155**	(0.043)	0.929**	(0.086)
Selected area supply variables						
Physician-to-population ratio	−6.30	(12.98)	−6.89	(11.16)	−48.02*	(19.45)
Hospital-bed-to-population ratio	14.06*	(6.94)	−5.71	(5.83)	6.37	(11.33)
AAPCC rate	0.0006*	(0.0002)	0.0011**	(0.0002)	−0.00022	(0.00030)

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level.
[a] *Omitted from table*: results for census region, rural/urban residence, year of observation.
[b] Dependent variable was ln(inpatient days + constant).
[c] 182 observations missing data on the dependent variable.

Table 4. Probability weight results[a]

	Coefficient	s.e.	t
$\varphi_{1\text{CLUSTER}}$	−5.51	2.31	−2.38
$\varphi_{2\text{CLUSTER}}$	−0.52	0.62	−0.83
$\varphi_{3\text{CLUSTER}}$	0.98	0.28	3.55
$\varphi_{4\text{CLUSTER}}$	0.501	0.33	1.501
$\varphi_{1\text{INDIVIDUAL}}$	1.43	0.203	7.03
$\varphi_{2\text{INDIVIDUAL}}$	2.05	0.29	7.05
$\varphi_{3\text{INDIVIDUAL}}$	2.28	0.26	8.89
$\varphi_{4\text{INDIVIDUAL}}$	1.67	0.28	5.89

[a]Probabilities for mass point 5 are equal to $1 - \sum_{j=1}^{4} \varphi_j$.

Table 5. Mass point results[a]

	Coefficient	s.e.	t
$\lambda_{2\text{CLUSTER}}$	−1.051	2.66	−0.40
$\lambda_{3\text{CLUSTER}}$	−1.051	0.302	−3.48
$\lambda_{4\text{CLUSTER}}$	0.46	0.13	3.70
$\lambda_{2\text{INDIVIDUAL}}$	−0.95	0.10	−9.68
$\lambda_{3\text{INDIVIDUAL}}$	0.17	0.13	1.33
$\lambda_{4\text{INDIVIDUAL}}$	1.031	0.14	7.54

[a]Mass points 1 and 5 normalized to 0 and 1, respectively.

Table 6. Mass point results and associated probabilities, by distribution level[a]

Point number (m)	Probability (ω_m)	Mass point value (η_m)
Cluster-specific distribution		
1	0.17	0
2	0.00068	0.26
3	0.1011	0.26
4	0.45	0.61
5	0.28	1
Individual-specific distribution		
1	0.036	0
2	0.15	0.28
3	0.28	0.54
4	0.35	0.74
5	0.19	1

[a]Variance of cluster factor: 0.12; variance of individual factor: 6.46.

coded with a "yes" value, the mean drops to 7.57 days. This is a reduction of 5.88 days (43.7%).

HMO membership had a positive and statistically significant effect on the probability of seeing a physician at least once during the year ($\beta = 2.37$, $p < 0.01$, see Table 3). The average of the predicted probabilities when all observations were coded with a "no" value for the HMO variable was 74.9%. When all were given a "yes" value, the probability rose to 89.0%, an increase of 14.1 percentage points (18.8%).

The auxiliary analyses, in which the model was rerun on the small and big panel datasets using instrumental variables estimation, produced results that were broadly consistent with the discrete factor results (see Table 7). However, the differences in the number of inpatient days and the probability of a physician visit only attained statistical significance in the discrete factor model. Among the possible reasons for the variations in significance levels across the estimations are the differences in sample size; the fact that the big panel dataset included persons who died; the higher precision of the discrete factor model relative to instrumental variables due to its use of full information maximum likelihood estimation; and the inclusion of survey weights in the small panel regression. It was not possible to do a weighted analysis for the big panel because the MCBS does not provide three-year backward longitudinal weights for use on a panel that includes persons who were not in the MCBS sample for all 4 years.

Discussion

The effect of Medicare HMOs on utilization

This study hypothesized that Medicare HMO enrollees would have slightly lower health services utilization than nonenrollees after controlling for sociodemographic and health status differences. While studies from the 1980s found significant effects of Medicare HMOs on utilization, those studies were conducted in an era in which favorable selection into HMOs was clearly present, and the study methodologies did not contain good controls for selection bias. Thus, some of the effects attributed to the HMO practice setting may actually have been due to the fact that the baseline health of the Medicare HMO enrollee population was better than that of the fee-for-service population. The present study utilized data from an era in which favorable selection may be less of a concern and included strong controls for any persistent selection bias that might exist; thus, the

Table 7. Predicted values of dependent variables[a]

	Mean probability of hospitalization	Mean number of inpatient days	Mean probability of physician visit
Naïve estimation on large panel			
Baseline when HMO variable coded "no" for all observations	15.63%	13.48 days	78.00%
Change when HMO coded "yes" for all	−9.22 pp (−58.99%) ($p<0.01$)	−5.85 days (−43.38%) ($p<0.01$)	+3.98 pp (+5.11%) ($p<0.01$)
Discrete factor estimation on large panel			
Baseline when HMO variable coded "no" for all observations	18.76%	13.45 days	74.89%
Change when HMO coded "yes" for all	−11.18 pp (−59.59%) ($p<0.01$)	−5.88 days (−43.70%) ($p<0.01$)	+14.10 pp (+18.83%) ($p<0.01$)
Instrumental variables estimation on large panel			
Baseline when HMO variable coded "no" for all observations	20.36%	13.53 days	78.28%
Change when HMO coded "yes" for all	−9.46 pp (−46.46) ($p<0.01$)	−5.89 days (−43.50%) (NS)	+2.12 pp (+2.71%) (NS)
Instrumental variables estimation on small panel			
Baseline when HMO variable coded "no" for all observations	16.68%	10.36 days	82.94%
Change when HMO coded "yes" for all	−10.56 pp (−63.31%) ($p<0.01$)	−3.45 days (−33.30%) (NS)	−2.53 pp (−3.05%) (NS)

[a] pp = percentage point.

residual effect of HMOs on utilization identified by the study was hypothesized to be fairly modest.

The study found, however, that even when selection bias is controlled for, Medicare HMOs significantly reduced the probability that a Medicare beneficiary would be hospitalized in a given year ($p<0.01$ for all estimations). HMO membership decreased the average probability of hospitalization by 11 percentage points in the discrete factor estimation, which represented a 60% reduction. (The reductions were less dramatic in the estimations using the small panel dataset, which excluded people who died. However, given the increase in hospital use during the period prior to death, the dataset including people who died seems to be most relevant.) In contrast, Langwell and Hadley's study of the early years of the Medicare risk program identified a 14–25% reduction in hospital use due to fewer admissions attributable to Medicare HMOs [5]; the RAND study of working age persons in HMOs found a 40 percent decrease in hospital admissions [11]; and Brown and colleagues found no appreciable effect of Medicare HMOs on hospital admissions [17].

The present study found that Medicare HMOs also reduced the mean number of inpatient days used by those persons who were hospitalized. The effect was statistically significant in the discrete factor model estimation, but not in the big panel or small panel instrumental variables estimations. The magnitude of the effect in the discrete factor estimation using the large panel data set was fairly large, on the order of a 5 day (43%) decrease. Previous studies of Medicare HMOs found that HMO membership was associated with a 16.8% decrease in length of stay [17]. Studies of non-Medicare HMOs typically find reductions in hospital days in the 10–40% range [11,30]. The HMO effect achieved statistical significance in most, but not all, prior studies. The results of the present study with respect to inpatient days, while somewhat variable across datasets, generally indicate a comparable or larger HMO effect than that identified in other studies.

This study determined that HMO membership increases a Medicare beneficiary's likelihood of seeing a physician on an outpatient basis at least once during the year. In the discrete factor model, the increase was 14 percentage points (19%), which was significant at the 1% level. However, in the instrumental variables estimations the change did not achieve statistical significance.

Previous studies generally have failed to find a significant effect of HMOs on physician visits [12]. Brown and colleagues found that Medicare HMO members had a 5% higher probability of seeing a physician at least once (but a slightly lower probability of having one or more physician visits per month) [17]. The hypothesis that the observed effect of HMOs on utilization in this study would be lower than that in previous studies was not proven correct for physician utilization. This study originally set out to model the total number of physician visits, but we were unable to do so because of data constraints (namely, the unreliability of MCBS data on total number of physician visits for HMO members, who do not have claims documentation of their usage). It should be noted that it is possible that HMOs may increase the likelihood of seeing a physician but decrease the total number of physicians in a given year, leading to a net reduction in physician utilization.

Study limitations

The limitations of this study's methodology should be taken into consideration when making inferences based on its results. One limitation arises from the data in the Medicare Current Beneficiary Survey, which may underreport actual health care utilization as discussed in the data section. For individuals in fee-for-service plans, the MCBS reconciles survey reports of utilization with administrative claims data in order to account for this problem. For HMO members, however, there do not exist detailed administrative data with which to perform this adjustment. Thus, the HMO members' data may disproportionately underreport utilization. A matching study of Medicare Current Beneficiary Survey data found that only 54% of health care events from fee-for-service Medicare bills could be matched to survey records [31].

In this study, utilization variables from the MCBS were selected in such a way as to minimize possible reporting bias. On the advice of an expert on the MCBS who indicated that HMOs do not report reliable administrative data on physician utilization, a physician visits variable that was based solely on survey reports was used. While there may be underreporting on this variable, the magnitude of the underreporting should be the same for HMO members and fee-for-service individuals. Moreover, since the physician visits variable was a simple binary indicator, it seems relatively unlikely that there would be a great deal of inaccurate recall: Most people can remember whether or not they saw a physician at least once during the last 4 months.

The MCBS expert indicated that HMOs do report fairly reliable administrative data on hospitalizations, so unreconciled claims data were used for the probability of hospitalization variable and the inpatient days variable. To investigate whether these administrative data might underreport or overreport hospital use, a manual check was performed of the degree of correspondence between unreconciled claims data and reconciled claims/survey data for the binary hospitalization indicator. The match rate was found to be near 98%, suggesting that the claims data are reliable. It was not possible to perform a similar check for the inpatient days variable because the MCBS does not publicly report interview data on the number of inpatient days. Thus, the possibility that there is reporting error in the inpatient days variable cannot be completely ruled out.

A second study limitation relates to generalizability. It is quite possible that the effect of being in an HMO on an individual's utilization varies across individuals. When treatment effects are heterogeneous, it cannot be assumed that instrumental variables estimates of the treatment effects are generalizable to the entire population represented by the sample [32,33]. Rather, the estimates are determined by variation in utilization among a subgroup of individuals whose participation in an HMO depends on the value of the instrumental variable, HMO market penetration. Put another way, the estimated effects apply over the range of market penetration in the sample only.

Policy implications

This study found that when simultaneous equations methods are used to control for possible selection bias, Medicare HMOs significantly decrease both the probability of hospitalization and the number of inpatient days for those hospitalized, but increase the likelihood of having some physician utilization. It is unclear from this study how this reduction in hospital *use* translates into a reduction in *costs* or whether there were any effects on appropriateness of care. Without information about the specific nature of the hospitalizations that were avoided or shortened by HMOs, it is difficult to extrapolate from hospital days avoided to costs avoided. As a general matter, there is empirical evidence that the lower rates of hospital admissions among HMO members are not confined to discretionary hospitalizations, but rather cut across all hospitalization categories [12,34]. If HMOs do reduce hospitalization rates across the board, then one would expect to see the reduction in hospital use translate into a reduction in hospital costs of approximately equal magnitude.

One must be cautious in interpreting this finding in terms of cost savings *to the Medicare program.* Even if we assume that Medicare HMOs are able to achieve a significant reduction in hospital costs, this does not necessarily mean that Medicare is saving money. Medicare's savings depend on the level of reimbursement given to HMOs by the AAPCC payment formula, and whether there is any lingering favorable selection that makes this formula inadequately risk-adjusted. The AAPCC at the time of this study was geared to save Medicare 5% of its total costs – that is, Medicare HMOs were paid 95% of what HCFA estimated it would cost to care for a Medicare beneficiary with that risk profile in the fee-for-service sector. If no favorable selection exists on a risk factor not represented in the payment formula, then under this scheme the Medicare program will indeed save 5%. If Medicare HMOs are able to reduce hospital costs by more than 5%, the HMOs keep the difference (though they are required by law to devote it to reducing Medicare enrollees' premiums or expanding their benefits packages). Assuming no selection bias problem, Medicare saves exactly 5% due to the Medicare risk program under this reimbursement formula.

Does this reimbursement formula overpay CMS risk contractors? The Clinton Administration appeared to believe so as it proposed to reduce the rate of reimbursement to 90% [35]. More recently, the Balanced Budget Act of 1997 altered the structure of the payment formula and provided for implementation of additional risk adjustment based on diagnostic data beginning in 2000. The Balanced Budget Act reforms mean that HMOs are no longer uniformly paid 95% of the estimated fee-for-service cost. Rather, the ratio varies across counties and was estimated to be 98–119% in 2000 [36]. Historically, when analysts have talked about the overpayment problem, they have been referring to overpayment arising from favorable selection into Medicare HMOs. That is, they have been speaking of the disjunct between a reimbursement formula that is based on the *average* cost of caring for beneficiaries in the fee-for-service sector and the fact that, at least in the early years of the Medicare risk program, the beneficiaries who chose to join HMOs were much healthier than the average beneficiary. There is a second sense in which CMS could overpay its risk contractors, however. Even if one assumes completely neutral selection, a reimbursement rate based on a given proportion of the cost of average cost of caring for beneficiaries in the fee-for-service sector may be too high if HMOs are actually able to care for their Medicare enrollees at a much lower cost than fee-for-service plans.

This study does not provide direct evidence for or against the proposition that HCFA may have overpaid Medicare HMOs during the study period in this sense, because this study did not use costs as its metric for measuring the effects of HMOs on utilization. The study's findings do suggest, however, that HMOs are able significantly to reduce the amount of inpatient care consumed by Medicare beneficiaries, raising a genuine issue as to whether risk contractors may be compensated too generously. This question merits further investigation in the form of studies that measure the effects of Medicare HMO membership on hospital costs, rather than on the probability of hospitalization and the number of inpatient days.

It is important to consider, when weighing additional risk adjustments to the AAPCC payment formula, that Medicare risk plans are required by law to devote profits to providing extra benefits for their subscribers. To the extent that the profits of some plans will be reduced by further risk adjustment, these plans will not be able to offer additional services and may have to roll back existing benefits or impose or raise premiums. Managed care involves heightened administrative burdens, relative to fee-for-service Medicare, for those who seek access to specialist and inpatient care. Risk plans will attract beneficiaries only to the extent that they offer compensating benefits of the kind normally available only through supplemental insurance at a lower out-of-pocket cost than Medigap plans. Thus, if we want beneficiaries to continue to enroll in Medicare HMOs, it is crucial that the reimbursement system provide plans with sufficient revenue to continue to offer an attractive package of benefits at a low price.

In conclusion, this is an era in which CMS is engaging in broad experimentation with means of controlling costs in the Medicare program. Medicare managed care is but one of its experiments. The creation of the Medicare + Choice program is its most recent foray into alternative financing and delivery mechanisms. No doubt as the Choice program is implemented and evaluated, CMS will reassess the relative attractiveness of managed care. One aspect of this assessment is the efficacy of the program in saving money for Medicare. This study's findings are germane to that question, in that they suggest that HMOs are effective in reducing hospital utilization for the Medicare population. This suggests that managed care is a strategy worth preserving for Medicare, even if the means by which managed care organizations are reimbursed may require reform.

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